Modern Techniques in Acoustical Signal and Image Processing

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This article was submitted to 9th International Congress on Sound and Vibration, Orlando, FL., July 8-11, 2002

April 4, 2002





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This work was performed under the auspices of the United States Department of Energy by the University of California, Lawrence Livermore National Laboratory under contract No. W-7405-Eng-48.

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MODERN TECHNIQUES IN ACOUSTICAL SIGNAL AND IMAGE PROCESSING

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Abstract

Acoustical signal processing problems can lead to some complex and intricate techniques to extract the desired information from noisy, sometimes inadequate, measurements. The challenge is to formulate a meaningful strategy that is aimed at performing the processing required even in the face of uncertainties. This strategy can be as simple as a transformation of the measured data to another domain for analysis or as complex as embedding a full-scale propagation model into the processor. The aims of both approaches are the same---to extract the desired information and reject the extraneous, that is, develop a signal processing scheme to achieve this goal. In this paper, we briefly discuss this underlying philosophy from a "bottom-up" approach enabling the problem to dictate the solution rather than visa-versa.

INTRODUCTION

Perhaps the best way to start a paper such as this is through an example that will provide the basis for this discussion and motivate the subsequent presentation. The processing of noisy measurements is performed with one goal in mind---to extract the desired information and reject the extraneous. In many cases this is easier said than done. The first step, of course, is to determine what, in fact, is the desired information and typically this is not the task of the signal processor, but that of the phenomenologist performing the study. In our case, we assume that the investigation is to extract information stemming from acoustic signals either emanating from a source whether it be a submarine passively operating in the deep ocean or a vibrating structure responding to ground motion. Acoustic applications can be very complex especially in the case of ultrasound propagating through complex media such as tissue in biomedical or through

heterogeneous materials of critical parts in nondestructive evaluation (NDE) investigations. In any case the processing usually involves manipulating the measured data to extract the desired information, such as, location and tracking of a submarine, to failure detection for the structure, or tumor/flaw detection and localization in both biomedical and NDE.

Another view of the same problem is to decompose it into a set of steps that capture the strategic essence of the processing scheme. Inherently, we believe that the more "a priori" knowledge about the measurement and its underlying phenomenology we can incorporate into the processor, the better we can expect the processor to perform---as long as the information that is included is correct! One strategy is called the "model-based approach" provides the essence of model-based signal processing [1]. Some believe that all of the signal processing schemes can be cast into this generic framework. Simply, the model-based approach is "incorporating mathematical models of both physical phenomenology and the measurement process (including noise) into the processor to extract the desired information." This approach provides a mechanism to incorporate knowledge of the underlying physics or dynamics in the form of mathematical propagation models along with measurement system models and accompanying uncertainties such as instrumentation noise or ambient noise as well as model uncertainties directly into the resulting processor. In this way the model-based processor enables the interpretation of results directly in terms of the problem physics. The model-based processor is really a modeler's tool enabling the incorporation of any a priori information about the problem to extract the desired information. As depicted in Fig. 1, the fidelity of the model incorporated into the processor determines the complexity of the model-based processor. These models can range from simple implied non-physical representations of the measurement data such as the Fourier or wavelet transforms to parametric black-box models used for data prediction, to lumped mathematical physical representations characterized by ordinary differential equations to full physical partial differential equation models capturing the critical details of wave propagation in a complex medium. The dominating factor of which model is the most appropriate is usually determined by how severe the measurements are contaminated with noise and the underlying uncertainties. If the signal-to-noise ratio (SNR) of the measurements is high, then simple non-physical techniques can be used to extract the desired information. This approach of selecting the appropriate model is shown in Fig. 1 where we note that as we progress up the "modeling" steps to increase the SNR, the complexity of the model increases to achieve the desired results. In the subsequent sections of this paper, we will use the model-based framework to explain the various classes of acoustical signal processing problems and attempt to show at a simple level---how these schemes can evolve within this framework.

Suppose we have a noisy structural vibration measurement of a 10 Hz oscillation in random noise of the same magnitude and we would like to extract the information as shown in Fig 2a. Our first attempt to analyze the measurement would be to take its Fourier transform (implicit sinusoidal model) and investigate the various frequency bands for resonant peaks. The result is shown in Fig. 2b, where we basically observe a noisy spectrum and a set of potential resonances—but nothing conclusive. Next we apply a broadband power spectral estimator using an inherent black box model (implicit all-zero transfer function model) with the resulting

spectrum shown in Fig. 2c. Here we note that the resonances have clearly been enhanced and the noise attenuated by the processor, but their still remains a significant amount of uncertainty in the spectrum. Upon seeing the resonances in the power spectrum, we might proceed next to a gray box model (explicit sinusoidal model) to enhance the resonances even further as shown in Fig. 2d along with the estimated resonant frequencies obtain using a peak detector. Finally, we use this extracted model to develop an explicit model-based processor (MBP) by developing a set of harmonic equations for a sinusoid in noise and construct the MBP from these relations. The results are shown in Fig. 2e, clearly demonstrating the superiority of the model-based approach, when the embedded models are correct.

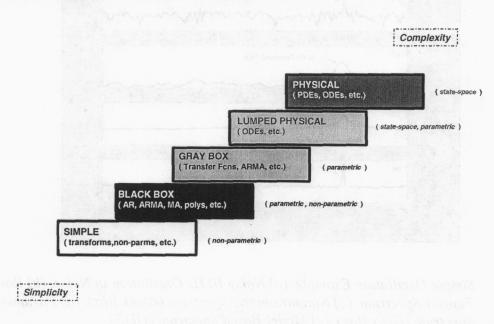


Figure 1. Model-Based Signal Processing: (a) Noisy data and 10 Hz Sinusoid. (b)
Fourier Spectrum. (c) Black Box Power Spectrum. (d) Gray Box Power
Spectrum. (e) Model-Based Power Spectrum.

MODERN SPECTRAL ANALYSIS

Classical spectral analysis is a very powerful example of a set of tools that have evolved in signal processing. Here a raw measurement is "transformed" to the spectral or Fourier domain for analysis. In terms of the model-based approach, we can consider this a "simple" transform when referring to classical nonparametric estimators [2]. However, modern techniques of spectral estimation can be considered both "black or gray-box" model-based processors or even physics-based processors depending on the underlying application. We call the black-box/gray-box methods parametric processors, since they employ a variety of underlying model sets to achieve their enhancement and improved spectral estimation. The parametric spectral estimator

consists of an estimator employed to estimate the parameters of the underlying model set and a power spectrum estimator using this model.

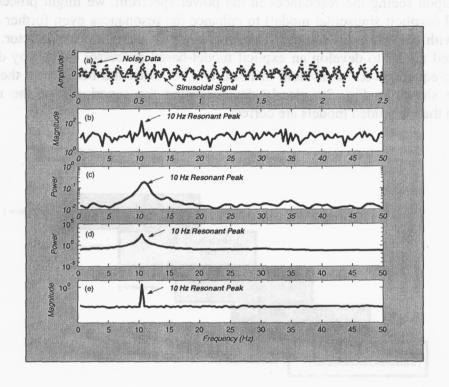


Figure 2. Simple Oscillation Example. (a) Noisy 10 Hz Oscillation in Noise. (b) Raw Fourier Spectrum. (c) Nonparametric Spectrum (Black Box). (d) Parametric Spectrum (Gray Box). (e) Model-Based Spectrum (ODE).

Modern spectral analysis techniques easily extrapolate to the space-time domain as long as we assume that the incoming wave front is separable in space (array) and time (or frequency). We can consider a measurement array in this context as a spatial sampler simply sampling the spatial portion of the arriving wave front. If we further assume that the temporal portion of the wave is restricted to a narrow frequency band, then we collapse its temporal response to a single line (in the Fourier space) that can be considered a parameter. So we see that the estimating the arrival angle in the case of a planar wave front or the source location in the case of a spherical wave front can be considered a problem of "spatial" spectral estimation and all of the usual techniques (with some restrictions) apply to the array signal processing problem as well. In acoustics, a large set of problems reduces to array processing or spatial spectral estimation in this context. Such problems as ocean acoustic (sonar) signal processing for direction-of-arrival (DOA) estimation or localization fall into this category along with ultrasonic NDE and biomedical processing. Clearly, seismic array processing, of which most of these ideas evolve, is a root application of arrays for epicenter location and velocity estimation. With this information

at hand, let us consider a simple example of a plane wave impinging on a sensor array to convey these ideas further.

A Simple Example

Consider the following example taken from ocean acoustics to motivate the modern approach. Suppose we have a plane wave signal characterizing an acoustic source measured by a horizontal array. The plane wave is at a 50 Hz temporal frequency and a bearing of 45° impinging on a 2-element array at a 10 dB SNR. We would we like to solve the problem of extracting the source bearing and temporal frequency parameters. The bearing/frequency estimation or equivalently localization problem can be considered a problem of estimating a set of parameters from noisy hydrophone measurements.

The classical approach to this problem is to assume that the signal is separable in space and time and select a single sensor channel to perform a temporal spectral analysis on the time series to estimate the temporal frequency parameter. The bearing can then be estimated independently by performing spatial spectral estimation or beamforming on the array data. A beamformer can be considered a spatial spectral estimator that is scanned over bearing angle indicating the true source location at the bearing of maximum power. The results of applying this approach to our problem is shown in Figure 3a demonstrating the outputs of both spectral estimators peaking at the correct frequency and bearing angle parameters.

The MBP is implemented by incorporating the plane wave propagation, hydrophone array, and noise models. However, the temporal frequency and bearing angle parameters are unknown and must be estimated. The solution to this problem is obtained by augmenting the unknown parameters into a MBP structure and solving the so-called joint estimation problem [1-3]. This is the parameter adaptive form of the MBP used in most ocean acoustic applications [4]. Here the problem becomes nonlinear due to the augmentation and is more computationally intensive; however, the results are appealing as shown in Figure 3b. We see the bearing angle and temporal frequency estimates as a function of time eventually converging to the true values of 50 Hz and 45° bearing angle. The MBP also produces the "residual or innovations" sequence, (shown in the figure) which is used in determining its overall performance, i.e., it must be statistically zero-mean and white for optimal performance [1-3,5].

Thus, in summary the classical approach simply performs spectral estimation temporally and spatially (beamforming) to extract the parameters from noisy data, while the model-based approach embeds the unknown parameters into its propagation, measurement, and noise models through augmentation enabling a solution to the joint estimation problem. The MBP also enables a monitoring of its performance by analyzing the statistics of its innovations sequence. It is this sequence the indicates the optimality of the MBP outputs. This completes the example.

IMAGE PROCESSING

Typical image processing techniques in acoustics consists of pre-processing the raw image data to provide enhanced signals as input to the image formation algorithm as well as post-processing of the two-dimensional image to enhance, extract, and classify certain features of

high interest. In this paper, we concentrate primarily on the same theme that we have used throughout, the development of image processors that incorporate more and more a priori information about the acoustics generating the data and its incorporation into a model-based imaging algorithm.

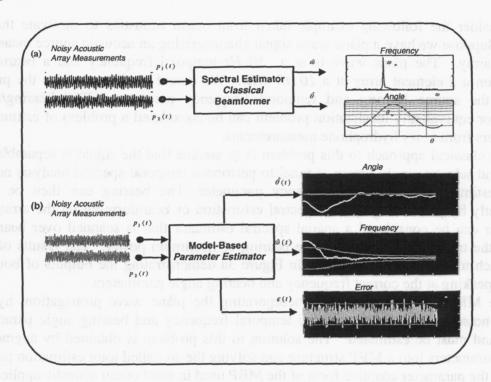


Figure 3. Plane Wave Impinging on a 2-Element Sensor Array---Frequency and Bearing Estimation Problem: (a) Classical Spectral (Temporal and Spatial) Estimation Approach. (b) Model-Based Approach using Parametric Adaptive (Nonlinear) Processor to Estimate Bearing Angle, Temporal Frequency and the Corresponding Residual or Innovations Sequence.

We saw in the previous example of a plane wave impinging on an array, how modern spatial spectral estimators (beamformers) can be used to estimate the wave's spatial and temporal spectral features. The model-based approach used all of the a priori information about the plane wave propagation and noise measurements to extract the parameters directly solving the problem. The same idea can be extrapolated to the imaging problem. We assume that we have an array of sensors either physical or synthetically created, and we have made a sequence of measurements resulting from exciting the medium under investigation. For instance, it can be an active sonar system in the ocean or an ultrasonic scanner in biomedical or NDE, or a passive array listening to an ocean surveillance volume for passing targets.

Here we consider acoustic application of data gathered from a laser ultrasound experiment for NDE. Our first approach is to apply the synthetic aperture focus technique

(SAFT) to image the part under investigation [6]. We assume that the flaws can be characterized by acoustic point scatterers in the near-field. Therefore spherical wave fronts impinge on our measurement array emanating from these flaws. The SAFT approach creates an image by assuming that the flaw location is at the given pixel of the image, *calculates* the associated propagation delays and attenuations assuming a homogeneous medium, *beamforms* the measured data based on these assumptions and *estimates* the power in the beam at the assumed location (pixel or point scatterer). This procedure is repeated for each pixel until the observed image is formed.

Another more acoustics-oriented approach for imaging is based on replacing the beamformer with a propagation model. The same scheme (as above) applies, but the propagation model generates the equivalent signal at the array and a criterion is created to "decide" whether a flaw is at a given test location (pixel or point scatterer). The propagation model can be as sophisticated as deemed necessary incorporating features such as both compressional and shear waves, multipath, dispersion, and noise. This model-based technique is called *matched-field imaging* (MFI) and enables the acoustician to use the a priori information available in a formal procedure to create the image [7,8].

Consider a typical laser ultrasonic application where a NDE is performed on a rectangular aluminum part with two flaws. The SAFT and MFI images are shown in Fig. 4. We note that the MFI approach incorporates both the compressional and shear wave fronts as well as the multipath caused by the part boundaries. The results of estimating the power at each pixel is shown where we see the high resolution and accurate results of the MFI compared to those of the SAFT processor.

CONCLUSIONS

We have discussed some of the modern techniques in acoustical signal and image processing. We have utilized the premise that the modern approach is to incorporate more and more of the a priori acoustical information available into the processing scheme, which typically takes the form of a mathematical model. The incorporation of this model into the processor leads to what is called the model-based approach or more recently the physics-based approach to processing. We started with a simple representation of the signal processing staircase showing that as the models get more complex so does the processor and used some simple examples to motivate the approach. We demonstrated some acoustic applications in sonar and NDE and compared results to the more classical approaches. Thus, we have demonstrated the philosophy of modern techniques in acoustical signal and image processing.

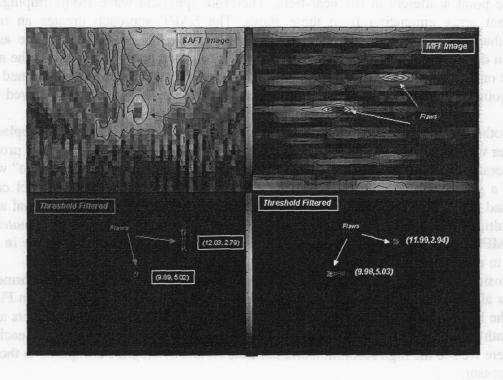


Figure 4. Acoustical Imaging of Laser Ultrasound Flaw Detection for NDE of Aluminum Part: (a) SAFT Imaging. (b) MFI.

REFERENCES

- [1] J. V. Candy, Signal Processing: The Model-Based Approach. (McGraw-Hill, New York, 1986)
- [2] J. V. Candy. Signal Processing: The Modern Approach. (McGraw-Hill, New York, 1988).
- [3] A. Jazwinski. Stochastic Processes and Filtering Theory. (Academic, New York, 1970).
- [4] J. V. Candy and E. J. Sullivan, "Ocean acoustic signal processing: a model-based approach." J. Acoust. Soc. Am., 92, (12), 3185-3201 (1992)
- [5] E. J. Sullivan and J. V. Candy, "Space-time processing of a moving array: a model-based approach." J. Acoust. Soc. Am., 102, (5), 754-765, (1998)
- [6] K. J. Langenberg, M. Berger, T. Kreutter, K. Mayer, and V. Schmitz. "Synthetic aperture focusing technique in signal processing." NDT International, 19, (3), 177-189 (1989).
- [7] .H. P. Bucker, "Use of calculated sound fields and matched-field detection to locate sound in shallow water," J. Acoust. Soc. Am., 59, 329-337 (1976)
- [8] A. Tolstoy. Matched Field Processing for Ocean Acoustics. (World Scientific, New Jersey, 1993).

ACKNOWLEDGEMENTS

This work was performed under the auspices of the U. S. Department of Energy by the University of California, Lawrence Livermore National Laboratory under Contract No. W-7405-Eng-48.